Detection and Analysis of Tremor Using a System Based on Smart Device and NoSQL Database.

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***Abstract*—Tremor is the most common symptoms of Parkinson's Disease (PD) and Essential Tremor (ET). Its detection and analysis during daily living plays a crucial role in the treatment of PD and ET patients. It is typically assessed in the clinic with certain tremor rating scales, which are qualitative, subject-dependent and do not necessarily reflect the real situation of the patient. In this paper, a system composed of a smartwatch, a smartphone and a NoSQL database sever is used to monitor the movements of the patients. A novel data analysis method is proposed to detect tremor and identify the connected actions. Tremor can be detected on the basis of the movement frequency difference and voluntary actions can also be recognized based on the rich information from the collected data. It helps clinicians to analyze the relationship between the tremor and a certain action. A series of simulated experiments are conducted to demonstrate the feasibility of the proposed system and data analysis method. The result shows that tremor happened during different situations can be detected with an adequate accuracy with the data collected by the proposed system. The actions around the tremor can also be identified.**

Keywords: tremor; smart device; NoSQL database; Parkinson's Disease; Essential Tremor; accelerometer

I. INTRODUCTION

Parkinson's Disease (PD) is a chronic, progressive, neurodegenerative disorder [1], [2]. It affects the movement of those suffering from the disease and it is typically characterized by a loss of motor function, increased slowness and rigidity [3]. Essential Tremor (ET) is another widely known disorder involving an action/posture tremor. Although ET is not a life threatening disease, it may result in functional disability and social inconvenience [4]. Tremor is the most common symptoms of PD and ET, which is one of the most common movement disorders encountered in clinical practice [5], [6], [7]. Tremor can be defined as a rhythmic shaking [8] or an involuntary oscillation [4] of a body part. The detection and analysis of tremor during daily living plays a crucial role in the treatment of PD and ET patients [9]. Currently, it is usually assessed in the clinic with certain tremor rating scales [2], [10], [11], [12], [13], [14]. While these rating scales have clinical utility, they require the presence of a clinician for scoring, are subject to clinical judgment and bias, and cannot be used for continuous monitoring of tremor fluctuation patterns throughout the day or in home environments [7], [9]. Previously, different methods have been developed to detect and quantify tremor. For example, accelerometers [15], [16], [17], [18], [19], [20], [21], gyroscopes [22], and electromyography (EMG) [23], [24], [25] have been used extensively to obtain quantitative measurements of tremor. Despite of the difference of devices and systems, all of these methods are focusing on the tremor itself. In fact, with the fast development of mobile computing and wearable technology, more information can be obtained to better analyze tremor.

In this paper, a human movement monitoring system based on smart devices and NoSQL databases [26] is used to collect data from individuals with tremor. Besides the tremor data, more related information is also collected with this system, such as the time, the location and the arm angle and so on. Using these data, not only the tremor can be detected quantitatively, but also the actions of the individual when the tremor happened. It is valuable in helping clinicians to find the relationships among different actions and tremor, and then to analyze the cause of tremor. A series of simulated experiments are conducted to demonstrate the feasibility of the proposed system and data analysis method. The result shows that tremor happened during different situations can be detected with an adequate accuracy with the data collected by the proposed system. The action around the tremor can also be identified.

The rest of this paper is organized as follows: an overview of the data collecting system and data analysis method is presented in section 2. The simulated experiments and results are described section 3. Conclusions of the paper are given in section 4.

II. METHODOLOGY OVERVIEW

A. Data Collecting System

The adopted movement monitoring system [26] is composed of three layers: (1) a Pebble smartwatch [27], which contains a tri-axis accelerometer and Bluetooth 4.0, for recording the user's arm movement data; (2) an Android smartphone for receiving data from Pebble and sending them to remote server after integrated with data collected from the GPS sensor and accelerometer inside the smartphone; (3) a NoSQL data search and analytic engine [28] on remote server for data storage and analysis. The structure of the collected data is as shown in Table I.

All the data collected from the smartwatch and smartphone are integrated in the smartphone and then uploaded to remote server through Internet. On the remote server, Elasticsearch [28], is used to manage the data received from the smartphone. It is a flexible and powerful open source, distributed, real-time

TABLE I. STRUCTURE OF DATA COLLECTED BY THE SYSTEM

Data name	Data source	Description
Acceleration	Pebble smartwatch	Acceleration values on three dimensions generated by the tri-axis accelerometer inside the smartwatch,ranging from -4000 mG to +4000 mG.
Arm angle	Pebble smartwatch	The angle between the arm and the ground level, ranging from -180°to +180°.
Time stamp	Pebble smartwatch	The time when the acceleration values are generated.
Frequency	Pebble smartwatch	The data collecting frequency of the accelerometer.
Location	Android smartphone	The latitude, longitude, altitude and accuracy values generated by the GPS sensor inside the smartphone. The last 3 parameters, px, py and pz, indicate the acceleration values on the three axes of the accelerometer inside the smartphone.
Acceleration	Android smartphone	The acceleration values on three dimensions generated by the tri-axis accelerometer inside the smartphone.
User records	Android smartphone	The feedback information from the user, such as the actions, time, tremor level etc.

search and analytic engine. NoSQL databases are developed to manage large volume and high complexity data produced due to the fast employment of smart devices [29], [30], [31]. A NoSQL database is adopted in our system instead of a classical relational database because NoSQL database in our system we will not only deal with structural data but also the non-structural data like natural languages to help analyze the behavior of human. Both the size and the type of data can not be defined in advance which requires the database to be very flexible. Classical relational database can not fill these requirements while the NoSQL database can solve these problems very well.

B. Data Analysis Method

The search service throughout the NoSQL database is managed by the middleware for agents speaking JavaScript Object Notation (JSON) [32] both living at the server as well as outside the server holding the storage service. It is convenient to export the data to different software for further analysis.
The main interests in this paper are not only to detect the tremor over large sequence of data but also to be able to identify the connected actions being carried out. Therefore, the data analysis includes three parts: action identification, tremor detection and background action recognition when tremor happens.

1) Action Identification: The movement frequency of human varies according to different actions or body postures. For example, the arm swing frequency during eating, walking and running are totally different. Besides, the movement habits, such as the walking speed, sleeping posture and eating rhythm, also differ among different individuals. All these differences can be reflected in the data collected by the system mentioned above. Therefore, it is possible to identify a certain action based on the collected data using Machine Learning techniques, which has been proved by many researchers[33], [34], [35]. In our case, several typical actions have been identified with adequate accuracy on the basis of a comprehensive consideration of location, movement frequency, arm angle and acceleration vales obtained from the collected data.

TABLE II. ACTIONS AND THEIR DESCRIPTIONS OF THE EXPERIMENT

Step	Action	Description	Duration
1	Stretch arms	Stretch the arms straight out from the body, shoulder high, and keep the hands facing the ground.	60 (s)
2	Bend arm	Bend the arm and keep the empty hand near the mouth to simulate the drinking action.	60 (s)
3	Drink simulation	Bend the arm and keep the hand with a cup near the mouth to simulate the drinking action.	60 (s)
4	Stretch arms with tremor	Stretch the arms straight out from the body, shoulder high, keep the hands facing the ground while simulating the tremor.	60 (s)
5	Bend arm with tremor	Bend the arm and keep the empty hand near the mouth as in step 2 while simulating the tremor.	60 (s)
6	Drink with tremor simulation	Bend the arm and keep the hand with a cup near the mouth as in step 3 while simulating the tremor.	60 (s)

2) Tremor Detection: The tremor of PD and ET patients occurs with frequency range from 4 Hz to 12 Hz, according to the difference of age, disease situation and body postures and so on [36], [37], [38], [39]. It is higher than the normal voluntary movements of human. As shown in Fig. 1, it is obvious that the movement amplitude between 4 HZ and 8 Hz is higher than the neighborhood frequency, and the voluntary movement frequency is lower than 1 Hz, where the amplitude is much higher. Thus it is possible to detect the tremor according to the frequency difference [4], [7]. It has also been proved that a tremor can be detected with the acceleration value collected from the wrist [3]. Therefore, in our case, the acceleration values collected from the smartwatch are used to detect tremor.

3) Background Action Recognition: When a tremor is detected, it is useful to know which is the background action or posture when the tremor happens. It can help the clinicians to analysis the cause of tremor and remind the patients to avoid certain actions which may result in tremor. In our approach, after a tremor is detected, the data collected during that period will be used to identify the background action. In the end, both the tremor and its background action can be recognized. More detailed data processing method is introduced in following sections using the data collected from a simulated experiment.

III. EXPERIMENT AND RESULT

A simulated experiment is conducted and the data collected during the experiment are analyzed to demonstrate the proposed tremor detection and analysis method. The subject is a 28 years old healthy male. During the experiment, the subject finished a series of actions as shown in Table II. He maintains each position during 60 seconds. This experiment is designed to simulate the drinking action of the patients. It is consist of six actions, which can be divided into two groups, with tremor and without tremor, to make comparison.
The first action, stretch the arm, is designed to test the basic tremor that happens to all human, no matter with or without PD/ET disease. The second action, bend the arm without load, is set up to compare with the third action, bend arm with load. The aim is to find out the impact of weight to the tremor. The experiment data are collected with the system mentioned above and then exported to R studio [40], [41] for further analysis.

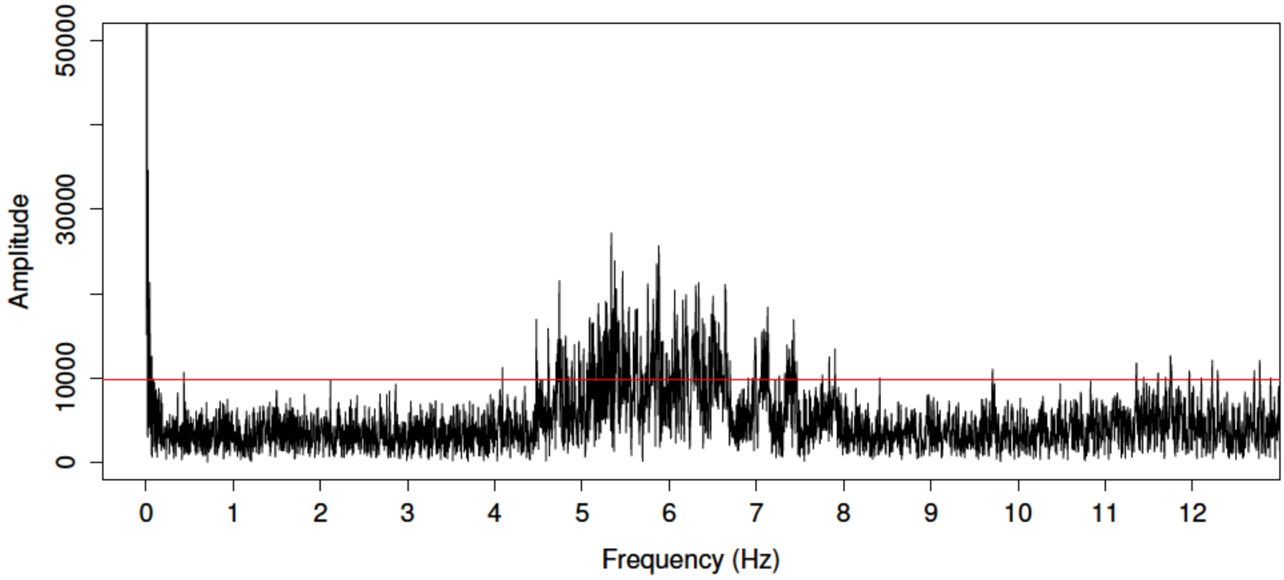

Fig. 1. Frequency difference between voluntary movement and tremor

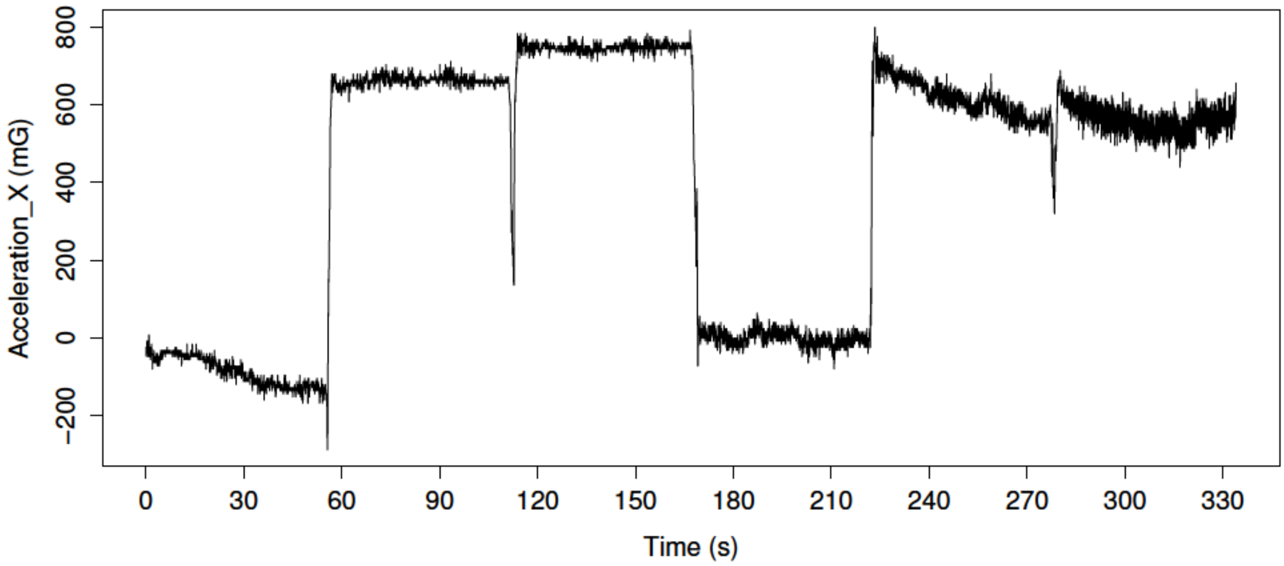

Fig. 2. Acceleration values on X axis

A. *Action Identification*

During the experiment, each of the six actions lasts for 1 minute and the data collection frequency is 25 Hz. The acceleration values on X axis, generated by the accelerometer of the smartwatch, during the experiment are plotted in Fig. 2. The difference among the six well defined actions are clear and obvious boundaries appear between each two actions.

The whole dataset contains 8350 records which is less than the theoretical amount due to the data transmit delay and data lose of caused by the hardware. The dataset is cut into 348 smaller chunks with length of 256 records (data generated in about 10 seconds) by a moving window. Then a Fast Fourier Transform (FFT) operation is applied to each of these data chunks and generate a new data matrix by combining the FFT results. Hereafter, a Principal Components Analysis is performed on the new FFT data matrix to extract the most relative features. As exhibited in Fig. 3, the first two components determine the most of the result. Therefore, the

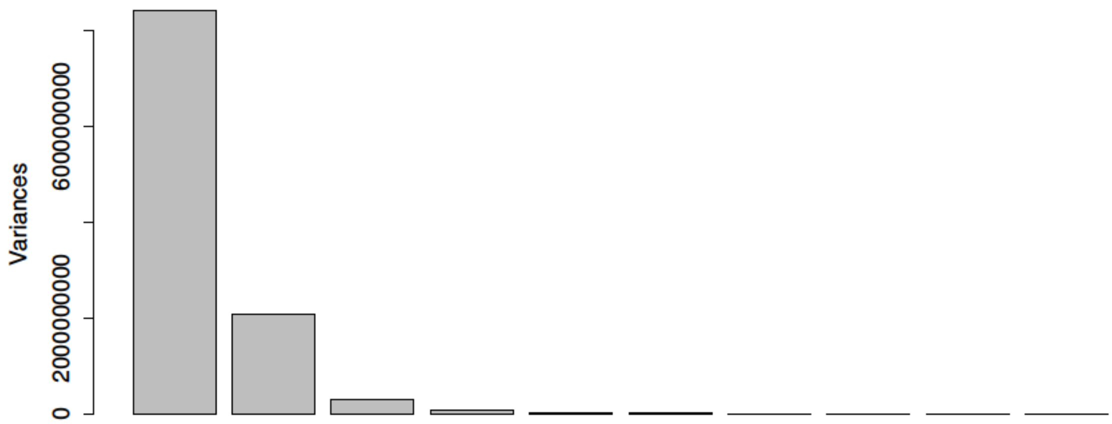

Fig. 3. Principal component analysis result

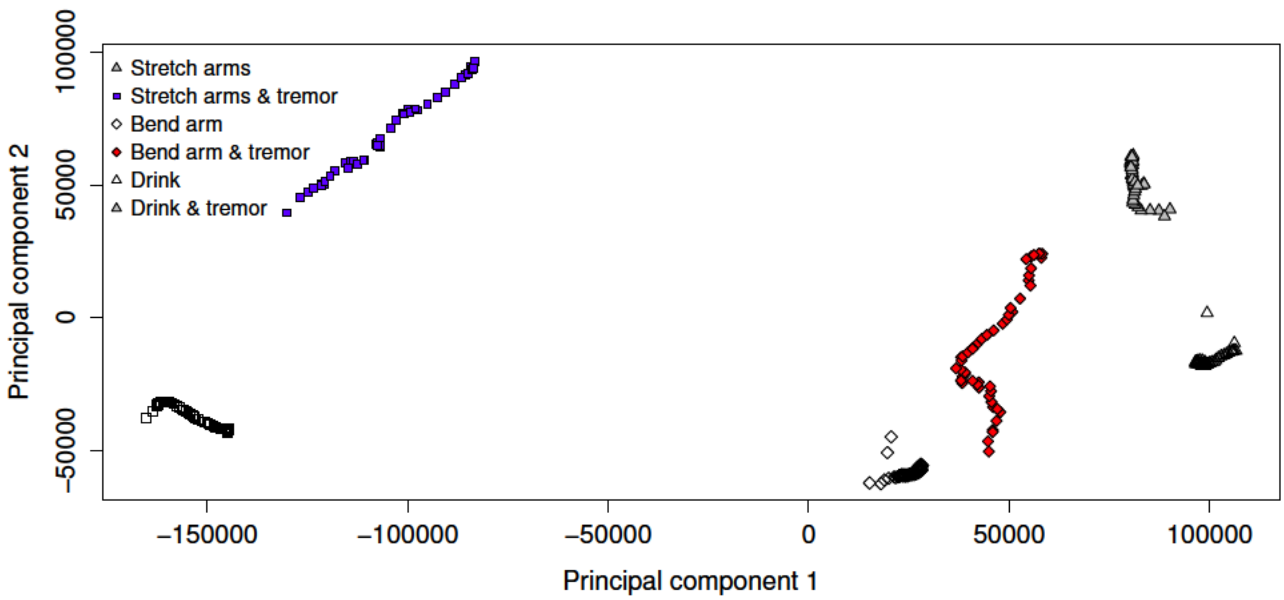

Fig. 4. Action classification based on the first two principal components

high intrinsic dimensionality features of the data chunks can be reduced into two dimensions. Fig. 4 shows the result after casting all the data chunks to the plane composed by these first two principal components. In Fig. 4, all the six actions are classified properly. The gap is very large between the first two actions, stretch arms with and without tremor, and the last four actions, bend arm with and without cup. While the difference among the last four actions is smaller. It makes sense considering the big difference of bending arm and stretching arm, and smaller difference between bending arm with and without cup. Besides, the impact of tremor to each action is also clear.

B. Detection of Tremor and Background Action

The tremor detection method is based on the frequency distribution of the collected data. As shown in Fig. 1, the frequency of tremor is different from voluntary movements. And the amplitude of tremor is higher than the instinctive shaking of the body. Therefore, the idea is to define a amplitude threshold and check if the amplitude in the tremor frequency range, 4 Hz to 8 Hz in this case, is higher than the threshold. If a higher amplitude is detected inside a certain data chunk, it can be considered as a tremor occurred.

Due to the large volume of the dataset, the first step of

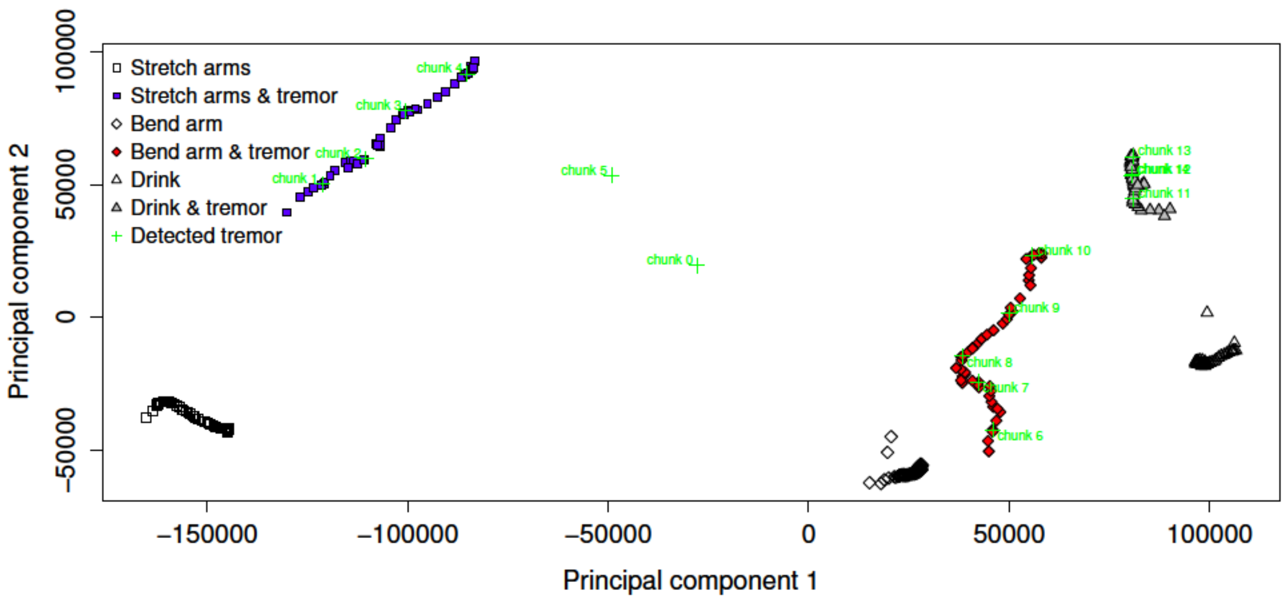

Fig. 5. Detected data chunk with tremor classification result

TABLE III. TREMOR DETECTION RESULT

Data chunk with tremor	Start time	End time	Data chunk with tremor	Start time	End time
Chunk 1	163 (s)	174 (s)	Chunk 9	245 (s)	255 (s)
Chunk 2	174 (s)	184 (s)	Chunk 10	256 (s)	266 (s)
Chunk 3	184 (s)	194 (s)	Chunk 11	266 (s)	276 (s)
Chunk 4	194 (s)	204 (s)	Chunk 12	286 (s)	296 (s)
Chunk 5	204 (s)	215 (s)	Chunk 13	296 (s)	307 (s)
Chunk 6	215 (s)	225 (s)	Chunk 14	307 (s)	317 (s)
Chunk 7	225 (s)	235 (s)	Chunk 15	317 (s)	327 (s)
Chunk 8	235 (s)	245 (s)	-	-	-

tremor detection is also data chunking. In order to improve the efficiency, different levels of chunks should be defined. For example, the size of the dataset is 8350 records in our case and two levels of chunks are defined. On the first level, the whole dataset is cut into four chunks with length of 2048 and a tremor detection operation is performed on these four data chunks. If tremor is detected on one of them, it will be further cut into smaller chunks with length of 256 and another round of tremor detection operation are performed. This method is useful in practical application, because the volume of dataset is much larger than experiment.

The threshold for tremor detection is calculated based on the data collected during the first action. Since the arm stays stable, the shake detected during this process is the instinctive shake of the body. The max amplitude value between frequency 1 Hz to 4 Hz is adopted as the threshold (the red line in Fig. 1) for detecting tremor.

In our case, the dataset is cut into chunks with length of 256 records, and after the tremor detection process, tremors are detected on 15 chunks. The start and ending time is listed in Table III.

The result shows all the tremors occurred after 163 seconds. When comparing with Table II and Fig. 2, it is clear that they all belong to the last three actions, which corresponds to the reality. There are several data holes among detected data chunks due to two possible reasons. The first reason is the tremor in the experiment is simulated. It is difficult for the subject to keep shaking at the same frequency and some times the shake may pause for a short time. Another reason is the length of the data chunks in this case is defined very short, which is 256 records corresponding to 10 seconds. In practical application, the length can be defined much longer to improve the accuracy.

With the rich information collected by the system, after a tremor is detected, it is also possible to identify the background action of each data chunk where tremor has been detected. The method looks to classify these data chunks with the action identification model built in last section. These data chunks are casted to the same plane composed by the first two principal components as in Fig. 4. The result is exhibited in Fig. 5, which shows that 13 of the detected 15 data chunks locate very close to the three actions with tremor and only 2 of them locate in the boundary. The accuracy of background identification is higher than 86%. This result is based on the simulated data while in reality the situation will be more complicated, which may result in the decrease of the accuracy. At the mean time, during practical application, the location and time information can also be considered separately, which on the other hand may increase the accuracy. This experiment is conducted to prove the feasibility of the proposed data collecting system and the data analysis method.

IV. CONCLUSION

A human movement monitoring system based on smart devices and NoSQL database is developed which can be applied to collect the tremor data of PD/ET patients and a novel tremor detection and action identification method is proposed in this paper. With the rich information collected by the system, not only the tremor can be detected quantitatively, but also the connected actions being carried out when the tremor occurs can be identified. It can help clinicians to analyze the causes of tremor and remind the PD/ET patients to avoid certain action that can result in tremor. The result of a simulated experiment demonstrates the feasibility of the proposed data collecting system and the data analysis method.

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